A database of ACT-R models of decision making

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Introduction

In a typical *two-alternative forced-choice* task of inference from memory, two objects are presented on a computer screen, which act as the *alternatives* among which a subject has to choose. Models of inference describe how *attributes* of those objects are used as *cues* to infer which of the two objects scores higher on a *criterion* of interest. Many models of inference have focused on describing not just what the outcome of this inference would be, but also which processing steps a decision maker would transverse to reach a decision. These models have increased substantially our understanding of the inferential process we follow (e.g., Bröder, 2012) and why this process is successful (Gigerenzer & Brighton, 2009).

However, some scientific question on inference from memory remain unanswered, because many models are frequently underspecified compared to the data that they are tested against. Cognitive mechanisms that remain underspecified include perception, motor action or a detailed memory theory. We argue that specifying all cognitive processes will help those models make precise predictions and address currently unaddressable questions.

The aim of this paper is to implement existing models of inference in the *cognitive architecture ACT-R* (Anderson, 2007), thus creating a database of publicly available *architectural process models of decision making*. We proceed with a brief description the classes of models that we include.

Models included in the database

Inferential models can be dichotomized, based on the type of information they rely upon, into *availability-based* and *cue-based models*. Following Newell and Bröder (2008), we further divide cue-based models into rule-based cue abstraction models, evidence accumulation cue abstraction models and configural models.

Availability-based decision models

We have included two availability-based models in our database: the *recognition heuristic* (Goldstein & Gigerenzer, 2002) and the *fluency heuristic* (Schooler & Herwtig, 2005). ACT-R implementations of availability-based models already exist (e.g., Marewski & Mehlhorn, 2011). However, we have included those for completeness. To make inferences, both of these models require only *declarative chunks* that represent the decision alternatives.

A Knowledge-based decision model

As a starting point, we include a general cue-based mechanism, which checks whether there is any knowledge present for the alternatives beyond availability and, if there is such knowledge for one alternative only, it selects that alternative (see Fechner et al., 2016).

Rule-based cue abstraction models

Cue-abstraction models operate on individual cues. These models retrieve cues one by one and make a decision when a decision rule is met. Among these models, we include fast-and-frugal heuristics (Gigerenzer, Todd, & the ABC Research Group, 1999), like *take-the-best* (Gigerenzer & Goldstein, 1996), Δ-*inference* (Luan, Schooler, & Gigerenzer, 2014) and *take-the-last* (Gigerenzer & Goldstein, 1999). We have also included more complex models, like the *weighted-linear model* (Gigerenzer & Goldstein, 1996). Some cue-abstraction models have already been implemented in ACT-R (e.g., Dimov, Marewski, & Schooler, 2013). All of these models require declarative chunks that store cue values of alternatives.

Evidence accumulation cue-abstraction models

Just like rule-based models, *evidence accumulation models* (Lee & Cummins, 2004) retrieve cues sequentially and require declarative chunks that store cue values. Unlike rule-based models, evidence accumulation models make a decision when enough evidence is accumulated in favor of one alternative or the other. We have implemented several such models, which differ in how they weigh cue values.

Configural models

Unlike cue-abstraction models, which require a separate chunk for each cue, configural models work on a set of cues. For example, *exemplar models* (e.g., Nosofsky, 1984) compare the *cue profiles* of alternatives (i.e., the set of cues associated with an alternative) to similar cue profile in memory and make inferences based on those profiles. We implement three different exemplar models. The first model evaluates each alternative based on a single similar exemplar, the second based on a weighted average of all exemplars in memory, while the third model considers fluency information. In addition, we include two *prototype models*, which differ in whether they evaluate the alternative based on a set of rules working on the entire cue profile (see Johansen & Kruschke, 2005) or based on fluency information.

In addition, we consider configural models which work with *cue-profile pairs*. These models are *instance-based learning theory* (Gonzalez, Lerch, & Lebiere, 2003) and *parallel constraint satisfaction* (Glöckner & Betsch 2008). In analogy to the exemplar implementations, we have created two instance-based learning models: the first retrieves the most similar cue-profile pair, while the second retrieves a weighted average of cue-profile pairs from memory.

Discussion and conclusion

We have provided a database of ACT-R implementations of models of inference from memory. These implementations provide comparable predictions, which can serve as a basis for model tests. Specifically, this database can be used, first, in model comparison simulations and, second, it can be utilized in future studies to identify decision processes using both behavioral and neural data. We expect that this will speed up addressing the currently present theoretical issues.

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